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**TECHNOLOGICAL LEADERSHIP,
HUMAN CAPITAL AND ECONOMIC
GROWTH: A SPATIAL
ECONOMETRIC ANALYSIS FOR U.S.
COUNTIES, 1969–2003***

by

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Abstract

The traditional view of cities as monocentric conglomerates of people clustered around an employment center, driving economic growth in cities that subsequently trickles down to the hinterland, is increasingly being challenged. In particular, the role of space, technological leadership, human capital, increasing returns to scale and industrial clustering as well as hierarchical organization principles have been emphasized in the more recent literature. This paper utilizes exploratory and spatial econometric data analysis techniques to investigate these issues for U.S. counties using data from 1969 through 2003. Ultimately, contiguous and hierarchical organization and interaction patterns are captured using an endogenous growth model allowing for spatial effects, inspired by earlier work on human capital and technology gaps. We investigate a neoclassical growth model and compare it to a spatial version of an endogenous growth model allowing for “domestic” investment in human capital and catch-up to the technology leader, and find that human capital strongly contributes to growth in a neoclassical setting, but much less so in an endogenous setting. In the endogenous model the catch-up term dominates in comparison to “domestic” human capital effects.

Key words: economic growth, human capital, technological leadership
JEL codes: C21, I23, O33, R12

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1. Introduction

The literature on economic growth has a long and rich tradition and harbors various different schools of thought. Recent literature reviews show that many empirical studies in the realm of the mainstream macroeconomic literature deal with economic growth at the country level, and they do not explicitly account for the influence of space (for a recent review, see Islam 2003). Gradually things are changing and a research tradition focusing on regions and applying spatial econometric techniques is emerging as well. Rey and Janikas (2005) summarize the literature on regional income inequality that predominantly uses exploratory spatial data analysis and spatial Markov-chains, and Magrini (2004) covers regional economic convergence studies using spatial econometric models. Abreu et al. (2005a) provide a detailed overview of both strands of literature, concluding that the former strand is relatively strongly embedded in the theoretical literature on growth, whereas the latter rests strongly on the application of spatial econometric techniques.

These reviews also show that spatial econometric models of regional economic growth are very much down-to-earth as far as their theoretical sophistication and their use of spatial econometrics is concerned.¹ Until recently, most studies were based on unconditional convergence models combining the use of exploratory spatial data analysis with standard spatial process models incorporating spatial autocorrelation in the errors or in the growth variable. Although the New Economic Geography literature stresses the significance of centrifugal and centripetal forces in the context of core-periphery models (Fujita et al. 1999), and the relevance of knowledge and human capital is well documented in mainstream economic growth theory, these aspects are still to be fully incorporated in empirical regional models of economic growth.

Much of the early work on U.S. economic growth focuses on the detection of convergence in growth patterns across the 48 contiguous states. In early studies, employing simple unconditional convergence models (Barro and Sala-i-Martin 1991) or occasionally a time series approach (Carlino and Mills 1993), the dominating perspective is neoclassical, although without a strong link to theory and, as far as spatial cross-section studies are concerned, without using appropriate spatial econometric techniques. Holtz-Eakin (1993) reinforces the link to theory by applying the neoclassical perspective due to Mankiw, Romer and Weil (1992; henceforth MRW) in an economic growth model pertaining to the U.S. states. In a slightly different fashion, Garofalo and Yamarik (2002) estimate a MRW model and concurrently

¹ Recently this is changing with regional studies increasingly showing a stronger theoretical basis as well as more involved spatial econometric specifications (e.g., Egger and Pfaffermayer 2006, Ertur and Koch 2005, Parent and Riou 2005).

introduce a new method to develop a capital stock series for U.S. states. Spatial econometric studies, such as Rey and Montouri (1999), explicitly incorporate spatial heterogeneity as well as spatial dependence, but they typically estimate an unconditional convergence model in the tradition of Barro and Sala-i-Martin (1991). The most recent trend in regional economic growth studies pertaining to the U.S. is to perform the analysis at a lower level of spatial aggregation, in particular at the county level (see Higgins et al. 2006, for an example). Although these studies are typically conditional convergence models, the selection of the conditioning variables is rather haphazard and oftentimes driven by (the lack of) data availability, in effect making the specifications regional Barro-type regressions.

In this paper we initially use the neoclassical MRW model as a theoretical basis for the specification of an economic growth model for U.S. counties, employing spatial econometric techniques to account for spatial heterogeneity and spatial dependence across counties. The MRW model emphasizes the role of human capital, but does not account for endogenous technological progress.² The model implicitly assumes technology to be a pure public good implying that the degree of technological sophistication as well as the rate of technological progress is equal across spatial units. This is rather unrealistic both at the level of nations as well as at the regional level. We therefore relax this assumption by explicitly incorporating a “domestic” technology or knowledge stock component proxied by human capital and a catch-up term following a Nelson-Phelps approach, specifically as outlined in Benhabib and Spiegel (1994). The latter accounts for catch-up towards the technology leader, where the technology gap is typically defined in terms of per capita income differences. We modify both the domestic and the catch-up term by including distance decay effects. Effectively, this results in a spatially explicit endogenous growth model. We incorporate the distance decay effect assuming that both contagious and hierarchical interaction across counties is relevant. Contagious interaction accounts for distance only, while hierarchical interaction accommodates the notion that interaction is more frequent among counties that have similar human capital stocks and technology levels (see, e.g., Parent and Riou 2005, for an application of the notion of contagious and hierarchical knowledge effects in the context of European regions).

In this paper we focus on regional economic growth at the level of counties in the U.S., which is a relatively low spatial scale level (see, e.g., Carlino and Mills 1987, Higgins et al. 2006, for county-level analyses). An analysis at the county level is attractive from a methodological perspective (increased efficiency in estimation) as well as from the viewpoint of policy-making, where development policies can be better tied in with detailed knowledge about local conditions. We also emphasize the theoretical basis of the growth equation by incorporating characteristic features of the traditional neoclassical perspective as well as an endogenous growth perspective. The use of an appropriately specified spatial econometric model makes it possible to account for unobserved spatial externalities, and increased possibilities to incorporate contagious and hierarchical distance decay patterns.

² To a certain extent the strict distinction between a neoclassical growth model, a Barro-type growth model and an endogenous growth model is not all that clear. In the empirics the distinction between the neoclassical MRW model and a Barro-type regression is not all that obvious, and in a sense it also not entirely clear whether a Barro-type model explaining steady state differences by other factors than physical and human capital amounts to a neoclassical convergence model or an endogenous model in which technology is explained. We also note that a strict interpretation of the MRW model at the regional level as a neoclassical model is at odds with the closed economy assumption on which the model is based.

The remainder of this paper is structured as follows. Section 2 reviews some of the recent literature on human capital and knowledge production. Section 3 describes the MRW framework and discusses the estimation results. Section 4 presents an extended version of the Benhabib and Spiegel (1994) model incorporating contagious and hierarchical distance decay effects and discusses the estimation results for this specification. Section 5 provides a summary and some concluding remarks.

2. Human capital and knowledge production

In the traditional neoclassical growth theory as developed by Solow (1956) and Swan (1956), output production is the result of both physical capital and labor. In modified versions of the model (e.g., MRW) capital is operationalized as human or physical capital. Labor input is hence decomposed in a quality component proxied by human capital of the worker and a quantity component measured in terms of hours worked (or some equivalent), both of which influence production. Human capital refers to the set of knowledge, skills or abilities which an individual acquires through his job, academic training and experience, and which increases that individual's value in the marketplace. Physical and human capital both have embodied characteristics. Individuals cannot be separated from their knowledge, skills, health, or values in the way they can be separated from their financial and physical assets (Becker 1975). Physical assets have embodied capacities that enable them to provide services or perform various tasks, but these capacities may exhibit vintage characteristics. Human capital has been recognized by many economists for increasing productivity and allowing individuals to generate a higher income. Generally human capital is generated in the form of knowledge that individuals acquire through investment. Knowledge can be produced in schools, universities and colleges and by institutions involved in R&D activities. Knowledge produced by schools, universities and colleges, and to some extent R&D laboratories may have both public and private good characteristics. The acquired knowledge is a public good when the produced innovation is not subject to any commercial activities and there are no property rights characteristics attached. When the produced innovation is subject to patent rights the knowledge or technology has a private good characteristic and represents the exclusive property of the inventor.

It is common in economic growth models to treat human capital simply as one of the right-hand side variables. Nelson and Phelps (1966) pointed out that by treating human capital simply as another input factor in economic growth accounting we may be misspecifying its role. The recent literature related to endogenous growth theory and the New Economic Geography has stressed the role of knowledge production and its spillover effects in driving long-run economic growth (see Romer 1986, 1990, Krugman 1991, Grossman and Helpman, 1990, 1994). Increasingly, empirical studies focus on knowledge creation, R&D activities and technological innovation as a determinant of local and regional economic growth, and R&D activities are often referred to as the main source of knowledge. It is also argued that entrepreneurship serves as mechanism facilitating the spillover of knowledge (Audretsch and Keilbach 2004). Acs et al. (2002) found that both university research and private R&D exerted substantial effects on innovative activity in U.S. metropolitan areas, with a clear dominance of private R&D over university research. With regard to the size of firms impacted by R&D activities, Acs et al. (1994) found that spillovers from university R&D contribute more to the innovative activity of small firms than to the innovative activity of large corporations. Audretsch and Feldman (1996), Jaffe (1989), Acs et al. (1992), Feldman (1994) and Anselin et al. (1997) also identified the existence of spatially mediated knowledge spillovers of R&D or academic research effects.

Other studies at the international and regional level have also confirmed the existence of positive correlation between growth and R&D expenditures (Coe and Helpman 1995).

In this paper we do not strictly follow the literature cited above, but instead we go back to the initial idea of “domestic” effects of the human capital stock on economic growth, and the role of catching up to the technology leader. Nelson and Phelps (1966) postulate that the technological progress depends on the educational attainment of the adopters, and on the gap between the theoretical level of technology and the level of technology in practice. It can therefore be expected that economies located closer to a technology leader benefit more and grow faster. Benhabib and Spiegel (1994) adapted the Nelson and Phelps (1966) model, incorporating the notions of domestic innovation and catch up. Their empirical results reveal that human capital has a positive and significant effect on total factor productivity growth when interacted with the distance to the technology leader measured in terms of per capita income. Below we extend the Benhabib and Spiegel approach with contagious and hierarchical distance decay processes, but first we concisely present the neoclassical MRW model and provide estimates for U.S. counties using this approach.

3. The MRW model

The MRW model starts from the neoclassical Solow model assuming a standard neoclassical production function with constant returns to scale. For a Cobb-Douglas production function with two inputs, capital and labor, the output at time t is given by:

$$Y_t = K_t^\alpha (A_t L_t)^{1-\alpha}, \quad (1)$$

where Y_t represents output, A_t the level of technology, K_t the stock of capital, and L_t the quantity of labor, all at time t . Equation (1) may be written in intensive form as:

$$y_t = k_t^\alpha, \quad (2)$$

where y_t and k_t represent the output and capital per effective unit of labor at time t , respectively. The model assumes that labor and technology grow exogenously at rate n and g , so that $L_t = L_0 e^{nt}$ and $A_t = A_0 e^{gt}$, where L_0 and A_0 represent the initial quantity of labor and level of technology.

Assuming that a constant fraction of output, s , is invested, we obtain the per capita output at the steady-state level as follows:

$$\ln\left(\frac{Y_t}{L_t}\right) = \ln(A_0) + gt + \frac{\alpha}{1-\alpha} \ln(s) - \frac{\alpha}{1-\alpha} \ln(n + g + \delta), \quad (3)$$

where δ is the depreciation rate.

Mankiw, Romer and Weil (1992) found that including human capital in the Solow model improves its predictive power of explaining cross-country growth rates. Furthermore, they argue that it solves to a large extent the omitted variable bias from which the non-augmented model

suffers. By introducing human capital in the Solow growth model, the per capita output at the steady state can be derived as follows:

$$\ln\left(\frac{Y_t/L_t}{Y_0/L_0}\right) = \ln(A_0) + gt + \frac{\alpha}{1-\alpha}\ln(s) - \frac{\alpha}{1-\alpha}\ln(n+g+\delta) + \frac{\beta}{1-\alpha}\ln(h) - \ln\left(\frac{Y_0}{L_0}\right), \quad (4)$$

where h refers to the stock of human capital and the other variables are defined as before.

The data used to operationalize and estimate the MRW model are for counties of the contiguous 48 states of the U.S. Several independent cities were incorporated with the surrounding counties, leading to a sample consisting of 3074 counties. The time period covered is 1969–2003. Nominal per capita incomes were obtained from the Bureau of Economic Analysis (BEA) and we subsequently adjusted the per capita income data for inflation using a regional Consumer Price Index series provided by the Bureau of Labor Statistics for four regions (West, South, Midwest and Northeast) making up the entire U.S. County population growth rates were computed from population data obtained from the BEA. No data at the county level are available for investments. We constructed a data series by allocating the national investment share of GDP of the U.S. from the Penn World Table by means of a county's average wage relative to the national average wage, and subsequent rescaling in order to ensure that regional investments add up to the national total. Educational data were obtained from the Economic Research Service (ERS) for 1970, 1980, 1990 and 2000. Human capital is defined as the proportion of the population 25 years and older with at least a 4-year college degree. All data series were averaged over the entire time period (either 1969–2003, or the observations for 1970–2000 for human capital).

The spatial weights matrix represents the topology of the system of U.S. counties, and is defined a priori and exogenously on the basis of arc distances between the geographical midpoints of the counties considered. It is a Boolean proximity matrix where elements are coded unity if the distance between counties is ≤ 100 miles, with subsequent standardization enforcing row sums to be equal to one.³ The spatial weight matrix has dimension 3,074, with 1.45% of the weights being nonzero, an average weight of 0.022, the minimum and maximum number of links between countries being 1 and 99, respectively, with an average of 45.

Figure 1 shows the spatial distribution of real per-capita income in 2003 (top) and the average annual growth of real per capita income over the period 1969–2003 (bottom) for counties of the lower 48 states. The highest per capita incomes in 2003 are found in the areas surrounding New York and Washington, some counties around the Great Lakes (particularly Chicago), around San Francisco and along the Pacific Coast in California, and some counties in Colorado and Wyoming. The area of counties with relatively low per capita incomes is concentrated in the Southeast extending to the Midwest, and the area surrounding Wyoming and Colorado going all the way to Texas in the south. In terms of per capita income growth we observe a distribution that is more or less reverse. Areas with high growth are rather scattered in

³ By convention the diagonal elements are zero. See Bell and Bockstael (2000) for a good explanation of the mathematical and statistical reasons for standardization. For a different viewpoint see Kelejian and Prucha (2005). The minimum cutoff distance required to ensure that each country is linked to at least one other county is 92.05 miles.

Colorado, Wyoming and New Mexico, on the northern edge in Minnesota, the Dakota's and parts of Wisconsin, and a vast area in the southeastern part of the country, excluding Florida.

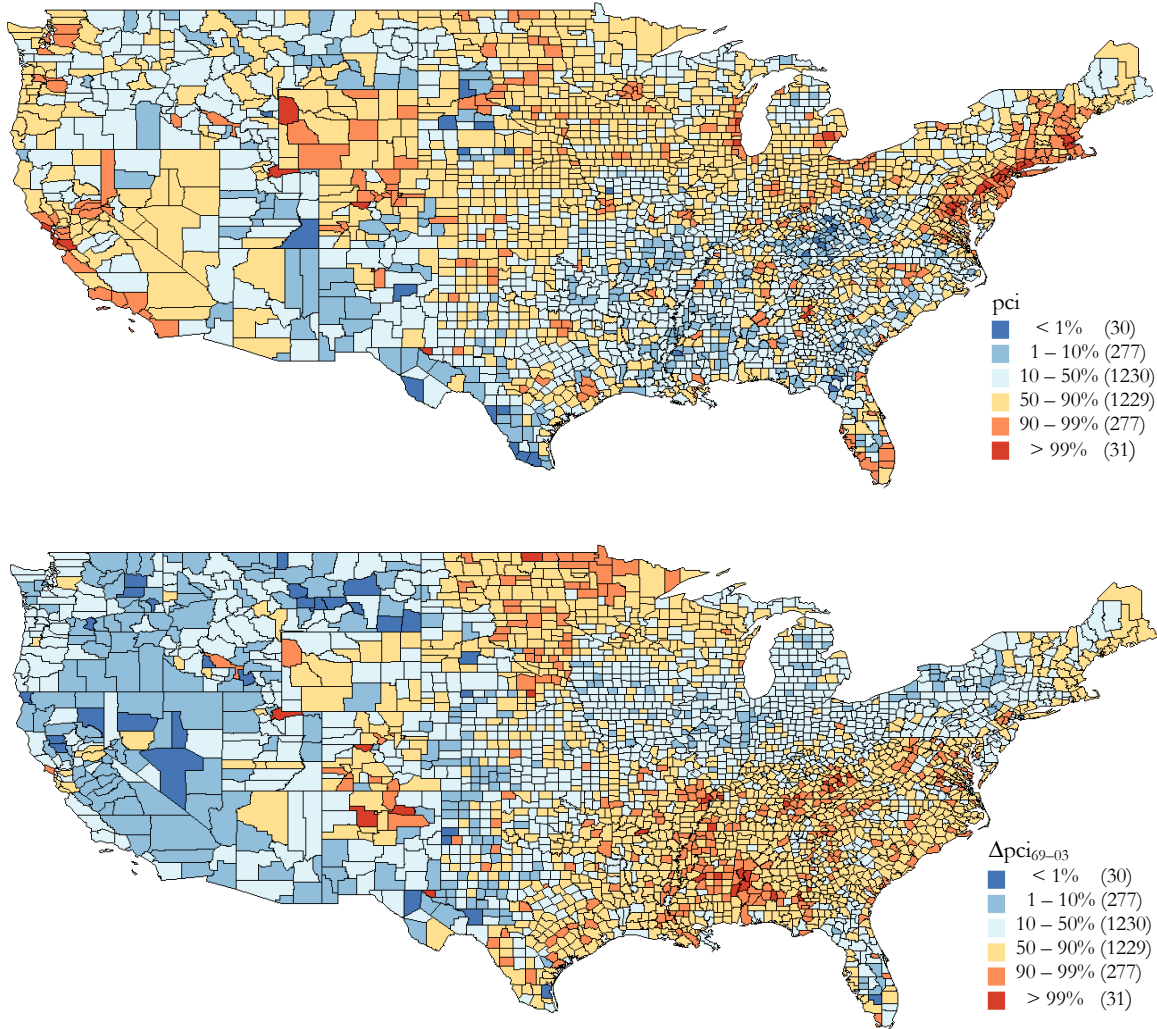


Figure 1. Real per capita income in 2003 (top), and average annual growth of real per capita income over the period 1969–2003 (bottom), counties of the 48 lower U.S. states

The top of Figure 2 shows the coefficient of variation and Moran's I for real per capita income.⁴ The coefficient of variation is relatively stable over the entire period, although there is a slightly

⁴ The coefficient of variation is defined as the standard deviation of x divided by the mean of x . With a standardized weights matrix Moran's I is defined as:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

where the variable x is measured in deviations from its mean, and w_{ij} are the elements of the weights matrix. The expected value of Moran's I equals $-1/(n-1)$, which is approximately -0.01 for our sample, signaling a random spatial allocation of the attribute values contained in x . Extensive details and principles for statistical inference are available in Cliff and Ord (1981) and Tiefelsdorf (2000).

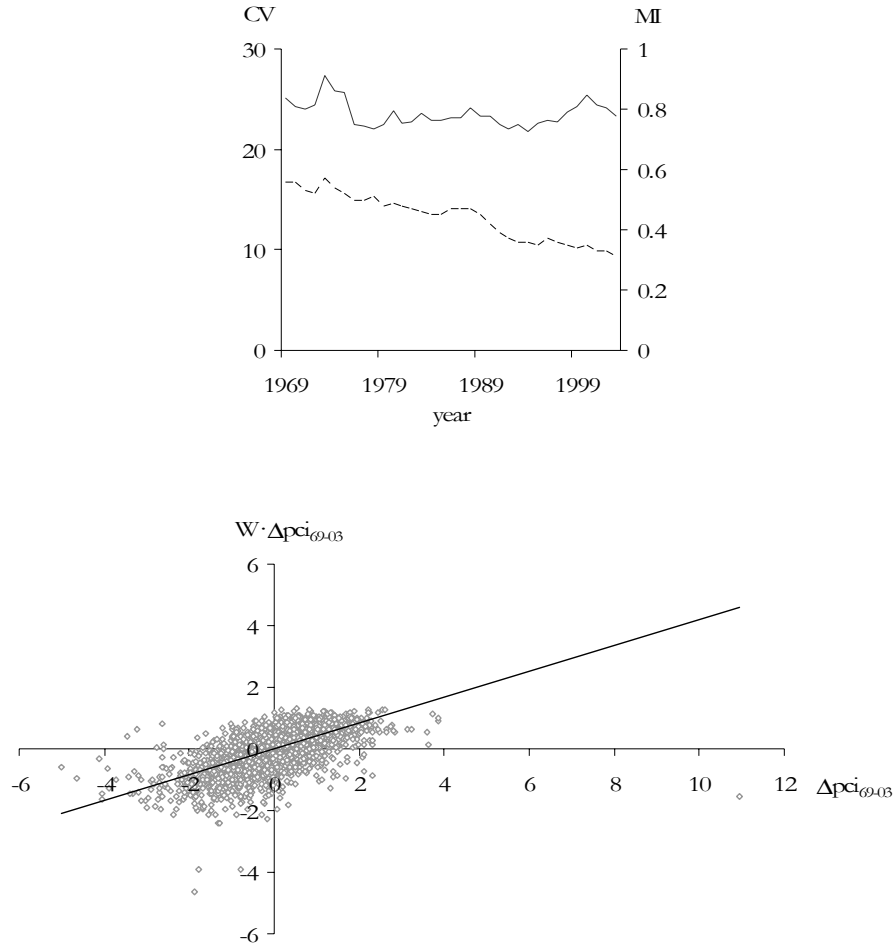


Figure 2. Coefficient of variation and Moran's I of real per capita income (top), and Moran scatterplot of the standardized average annual growth rate of real per capita income (bottom), counties of the lower 48 U.S. states, 1969–2003

decreasing trend indicating that there is σ -convergence. The degree of spatial clustering of real per capita income, as measured by Moran's I , shows an almost persistent downward trend. It starts at 0.56 in 1969 in order to decrease to 0.31 in 2003. The bottom of Figure 2 shows the Moran scatterplot for the standardized average annual growth rate of real per capita income over the period 1969–2003. The scatter diagram plots a standardized variable x_i against its spatial lag, which equals the spatially weighted average of the x_j -values with the set of neighbors being defined through the i -th row of the weights matrix, and aids in identifying local clusters of spatial correlation, spatial non-stationarity and outliers. The gradient of the trend line equals the Moran's I coefficient (see Anselin 1996 for details). The scatterplot shows a strong degree of spatial clustering of per capita income growth rates, for both above and below average growth rates. It should be noted that there is slightly more variation on the lower end of the distribution, where a few outliers occur for counties with relatively low growth rates that are surrounded by other counties with low growth rates (predominantly a few counties in Nevada). On the positive side there is a definite outlier, Loving county in Texas, which experienced an average growth rate of slightly over 7%.

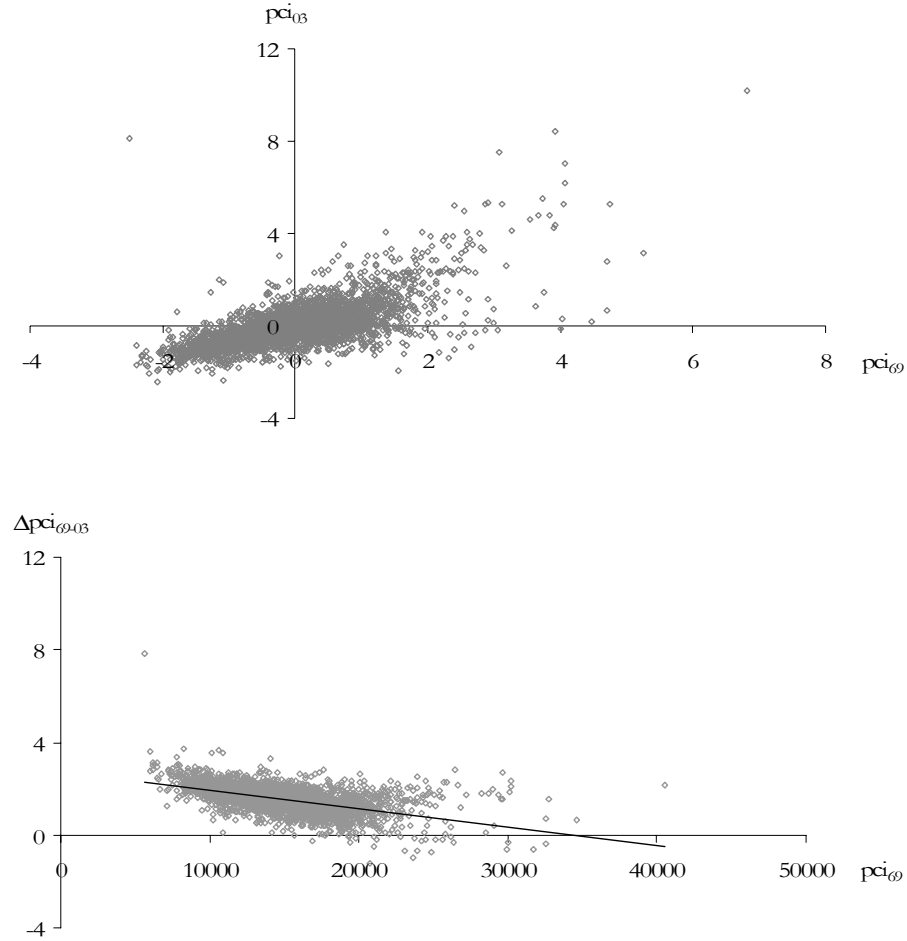


Figure 3. Standardized real per capita income in 1969 and 2003 (top), and the average annual growth rate of real per capita income over the period 1969–2003 against real per capita income in 1969 (bottom), counties of the lower 48 U.S. states

The top graph in Figure 3 shows the standardized real per capita income in 1969 and 2003. The concentration of points in the upper-right and the lower-left quadrants shows that the distribution of real per capita incomes is rather stable. Counties with above average per capita income levels in 1969 tend to have above average per capita incomes in 2003; likewise for counties with below average per capita incomes. The graph also shows that the variation on the upper end of the spatial income distribution is much less compact than at the lower end. On the lower end in 1969 Teton (Wyoming) is an outlier as it obtains one of the highest real per capita incomes in 2003. The bottom of Figure 3 shows the characteristic plot for unconditional σ -convergence, plotting growth against the level, with the decreasing trend line being indicative of convergence of real per capita incomes.

Table 1 provides the estimation results for the neoclassical MRW model. We start with simple ordinary least square (OLS) results for the unconditional growth model, the Solow model and the MRW model, including diagnostic test results, and subsequently present a specification allowing for spatially autocorrelated errors and spatial regimes (including groupwise heteroskedasticity) estimated by means of a General Moments (GM) estimator (Kelejian and Prucha 1999). The operational specification of the MRW model is given by:

$$\ln\left(\frac{y_t}{y_0}\right) = \beta_0 + \beta_1 \ln(y_0) + \beta_2 \ln\left(\frac{\bar{i}}{y}\right) + \beta_3 \ln(n + g + \delta) + \beta_4 \ln(\bar{h}) + \varepsilon, \quad (5)$$

where y_0 and y_t are real per capita income in 1969 and 2003, respectively, \bar{i}/y is the average of investments as a proportion of income, $(n + g + \delta)$ refers to annual population growth rate, the technology growth rate and the depreciation rate where the latter two together are assumed to amount to 5%, and \bar{h} is the average proportion of the population over 25 years with a higher education degree (as defined above).

Table 1. MRW specification with diagnostics for spatial effects, and spatial process models allowing for spatial dependence and heterogeneity^a

Models	OLS unconditional	OLS Solow	OLS MRW	GM-HET	
Variables	(1)	(2)	(3)	Slow (4a)	Fast (4b)
Constant	4.62*** (0.11)	5.75*** (0.14)	6.59*** (0.13)	4.55*** (0.30)	3.86*** (0.26)
GDP level 1969	-0.43*** (0.01)	-0.50*** (0.01)	-0.67*** (0.01)	-0.45*** (0.03)	-0.38*** (0.03)
Investment share		0.18*** (0.02)	0.13*** (0.02)	0.14*** (0.03)	0.05* (0.03)
Population growth		0.04*** (0.01)	-0.02** (0.01)	0.02 (0.02)	-0.07*** (0.02)
Human capital			0.20*** (0.01)	0.15*** (0.01)	0.14*** (0.01)
Spatial AR parameter				0.66*** (0.19)	
Convergence rate ^b	1.6	2.0	3.2	1.7	1.4
R^2 adjusted ^c	0.34	0.37	0.47	0.67	
AIC	-2876.14	-3010.93	-3573.79		
LIK	1440.07	1509.46	1791.90		
JB	4228.21***	3546.74***	6532.09***		
KB ^d	42.95**	47.64***	79.98***		
Chow-Wald ^e				630.69***	
I	0.25***	0.26***	0.27***		
LM-error	2580.28***	2738.87***	3138.83***		
Robust LM-error	1186.82***	1443.56***	1951.64***		
LM-lag	1457.44***	1329.27***	1219.76***		
Robust LM-lag	63.98***	33.96***	32.57***		
LM-SARMA	2644.26***	2772.83***	3171.40***		

^a Standard errors in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, ** and *, respectively.

^b In percents per year. The convergence rate equals $100 \times (\ln(b+1))/T$, where b is the estimated coefficient for the income level in 1969, and T the length of the 1969–2003 time period.

^c Squared correlation for GM.

^d Koenker-Basset variant of the Breusch-Pagan test with random coefficients as the alternative hypothesis.

^e The tests on equality of individual coefficients for the different groups are all significant ($p < 0.10$), except for the human capital variable ($p = 0.63$).

The results for the unconditional neoclassical growth model show the expected negative coefficient for the level of real per capita income, amounting to an annual convergence rate of 1.6%, which is in accordance with most of the literature (see Abreu et al. 2005b for an

overview). The results for the Solow growth model are similar in terms of convergence, and investments and population are significantly positively associated with income growth. This is counterintuitive as far as population growth is concerned. The MRW specification again shows similar results, although now population growth has the desired sign and human capital enters as an important determinant of economic growth. Although overall the model performs well, the diagnostics show that the null hypothesis of normally distributed errors is rejected and there is considerable heteroskedasticity, as signaled by the Koenker-Basset test based on random coefficients as the alternative hypothesis. Using the principles for checking for spatial autocorrelation outlined in Anselin et al. (1996), there is overwhelming evidence for errors following a spatial autoregressive process.

Given the presence of heteroskedasticity and spatial dependence we subsequently estimate the MRW model with spatial regimes determining parameter variation and groupwise heteroskedasticity. We distinguish the groups of fast- and slow-growing regions on the basis of above and below average growth rates, which effectively divides the sample in two approximately equal-sized groups. We estimate the model using a GM estimator because of the rejection of normally distributed errors, and because of inaccuracies involving the Jacobian term of such a large sample of observations (Kelejian and Prucha 1999). The results for the two groups, shown in columns (4a) and (4b), are fairly similar, with the exception of the population growth variable, which is significantly negative for fast-growing counties and not significantly different from zero for slow-growing counties. Although the results are fairly similar in magnitude, the Chow test rejects the null hypothesis for equality of coefficients across the groups. This is also the case for the individual coefficients except for the human capital variable, which is highly significant and of considerable magnitude (i.e., an elasticity of approximately 0.15) for both fast- and slow-growing counties.

4. A spatially explicit endogenous growth model

Although the MRW model performs reasonably well in the case of the U.S. counties, it suffers from various restrictive assumptions and does not explain technological progress. The latter can be achieved in various ways. Recently, Ertur and Koch (2005) extend the MRW model by assuming that technological progress is partly identical and exogenously determined for each spatial unit. In addition, they assume that the level of technology is determined by the amount of physical capital per worker, which generates knowledge externalities that eventually spillover to neighboring spatial units.⁵ We take a slightly different route and focus on spatial externalities embodied in human capital, extending the original work by Nelson and Phelps (1966) and Benhabib and Spiegel (1994). They start from a simple specification based on a Cobb-Douglas production function, which reads as:

$$(\log Y_t - \log Y_0) = (\log A_t - \log A_0) + \alpha(\log K_t - \log K_0) + \beta(\log L_t - \log L_0) + (\log \varepsilon_t - \log \varepsilon_0), \quad (6)$$

where Y_t is per capita income, K_t physical capital, L_t labor, A_t the level of technology, and ε_t an error term.

Concisely, the Benhabib and Spiegel (1994) version of the model assumes that the level of technology can be explained by the level of human capital “domestically” and a catch-up term

⁵ Ertur and Koch (2006) incorporate externalities of human capital as well.

that depends on the distance to the technology leader in terms of GDP per capita, and the level of human capital that is available to adopt the ideas and technologies originating from the technology leader. In formal terms:

$$(\log A_t - \log A_0)_i = c + gH_i + mH_i \left[\frac{Y_{\max} - Y_i}{Y_i} \right], \quad (7)$$

where $i (= 1, 2, \dots, n)$ indexes spatial units or regions, H refers to human capital, and Y_{\max} refers to the per capita income for the technology leader (i.e., the region with the highest per capita income). In a sense, Equation (7) can be seen as an a-spatial endogenous growth model which, after rearranging, reads as:

$$(\log A_t - \log A_0)_i = c + (g - m)H_i + mH_i \left[\frac{Y_{\max}}{Y_i} \right]. \quad (8)$$

Equation (8) shows that the capacity for “domestic innovation” depends on the available human capital stock. The human capital stock independently enhances technological progress and, holding human capital levels constant, counties with lower initial productivity levels will experience a faster growth of total factor productivity (assuming both m and $g - m$ are positive).

This model is strictly topological invariant, in the sense that changes in the size, shape and location of the areal units does not have a bearing upon the results. We therefore incorporate a spatial spillover effect in the available domestic human capital stock and a distance decay effect in the catch-up term, as follows:

$$(\log A_t - \log A_0)_i = c + gH_i + r \sum_{\substack{j=1 \\ j \in J_i(d)}}^J \frac{1}{d_{ij}} H_j + m \frac{H_i}{d_{i,\max}} \left[\frac{Y_{\max} - Y_i}{Y_i} \right], \quad (9)$$

where counties within a specific distance (the ‘cut-off distance’ d) are included in the $J_i(d)$ classes for the spatial spillover effect, and $d_{i,\max}$ represents the geographical distance of region i to the technology leader.

Equation (9) shows that there is a direct domestic effect of human capital accumulation, and in addition there are direct spillover effects from human capital accumulation in neighboring regions due to commuting effects and backward linkages. The catch-up term models the (domestic) growth rate of technology as a function of the existing gap with the (domestic) technology leader, and the pace of technology growth is conditioned on the domestic stock of human capital which determines the domestic capability of adopting state-of-the-art technology from the technology leader.

Rearranging and substitution gives:

$$(\log A_t - \log A_0)_i = c + gH_i - m \frac{1}{d_{i,\max}} H_i + r \sum_{\substack{j=1 \\ j \in J_i(d)}}^J \frac{1}{d_{ij}} H_j + m \frac{1}{d_{i,\max}} H_i \left(\frac{Y_{\max}}{Y_i} \right), \quad (10)$$

or alternatively,

$$(\log A_t - \log A_0)_i = c + \left(g - \frac{m}{d_{i,\max}} \right) H_i + r \sum_{j=1, j \in J_i(d)}^J \frac{1}{d_{ij}} H_j + m \frac{1}{d_{i,\max}} H_i \left(\frac{Y_{\max}}{Y_i} \right), \quad (11)$$

This equation may embody technology spillovers following both contagious and hierarchical spatial patterns. The “domestic term” shows that the productivity impact of human capital partly depends on the geographical distance to the technology leader, which assumes a contagious pattern of technology diffusion. The catch up term, however, represents a hierarchical technology diffusion pattern if it can be assumed that the technology leader will have a relatively high stock of human capital.

The structural equation shows that increasing the regional human capital stock independently increases total factor productivity, but more so in the case of geographical proximity to the technology leader. In addition there may be spatial spillovers of human capital stocks in neighboring counties. The catch-up term now signals that (holding human capital levels constant) counties with lower initial productivity levels experience faster growth of total factor productivity the closer they are geographically to the technology leader.

The reduced form shows that four terms affecting the growth of technology can be identified: (i) the domestic effect of human capital accumulation; (ii) a local contagious spatial spillover effect of human capital accumulation in proximate counties; (iii) a term signaling that the domestic productivity effect of human capital varies over space as it depends on the potential of contagion based interactions with the technology leader (i.e., the greater the geographical distance to the technology leader, the lower the domestic productivity of human capital accumulation); and (iv) a catch-up effect signaling that the magnitude of the (domestic) growth of technology varies depending on the size of the productivity gap with the technology leader, the level of the domestic human capital stock, and the geographical distance to the technology leader. The latter represents a hierarchical technology diffusion effect if there is a close correspondence between the technology gap and the difference in human capital stocks between the region under consideration and the technology leader.

One should note that the above reduced form specification contains an equality restriction on the effects associated with the domestic human capital productivity effect and the catch-up term. Moreover, the extended model is also only weakly topologically invariant in that it allows for the size and shape of areas to be different, but the results are no longer invariant to permutations of the location of the areal units. The marginal effects will depend on the location of a region in the spatial system, relative to its neighbors and relative to the technology leader.

Before presenting the estimation results of the above endogenous growth model we provide some insight into the spatial distribution of human capital across the U.S., and the technology leader(s) during the period 1969–2003.

Figure 4 shows a cartogram of population proportion with higher education throughout the period 1970–2000, for counties of the lower 48 U.S. states, with counties exceeding the 1.5

hinge in red⁶. It clearly shows that the spatial distribution is relatively stable, with obvious concentrations in the San Francisco area, around New York and Washington on the east coast, and in Colorado and New Mexico.

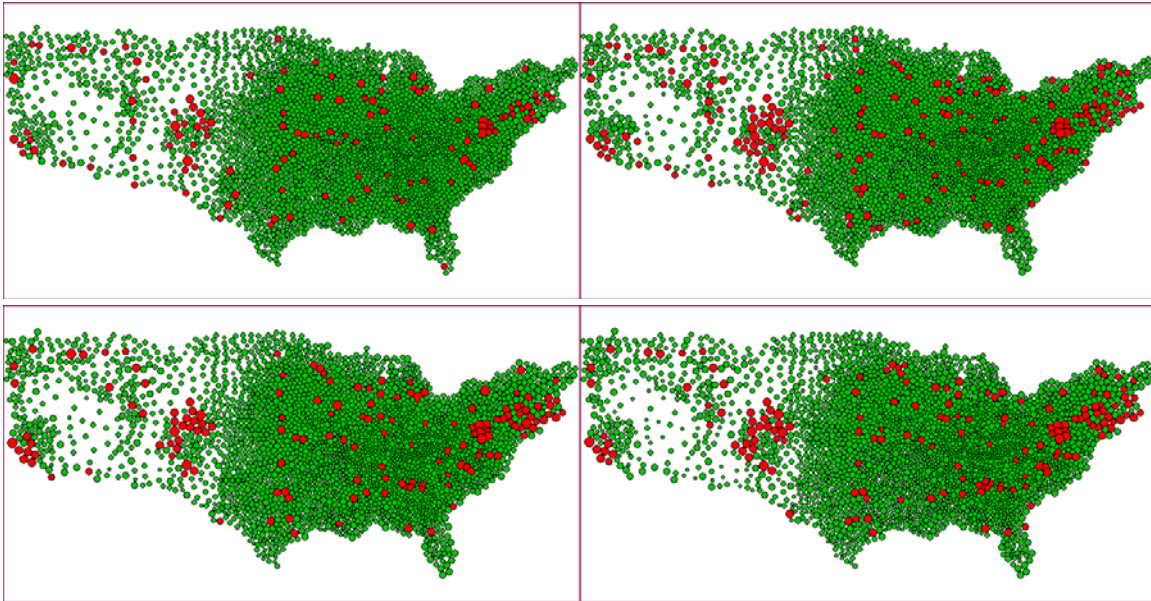


Figure 4. Cartogram of population proportion with higher education in 1970 and 1980 (top left and right), and 1990 and 2000 (bottom left and right), with those exceeding the 1.5 hinge in red, counties of the lower 48 U.S. states

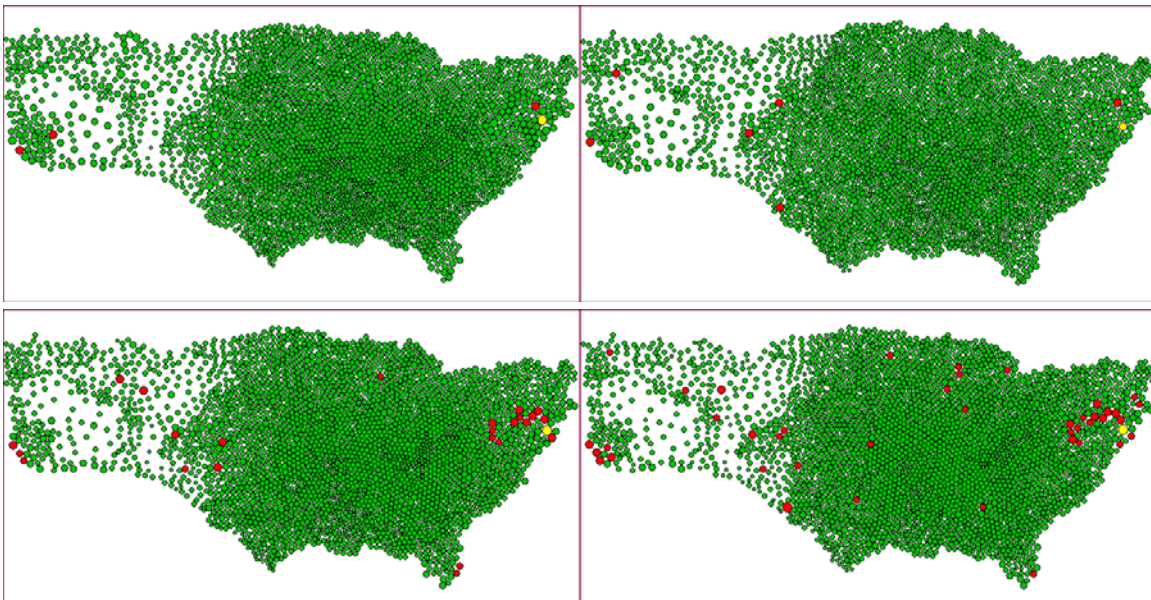


Figure 5. Cartogram of technology leaders as measured by real per capita income in 1970 and 1980 (top left and right), and 1990 and 2000 (bottom left and right), with those exceeding the 3.0 hinge in red, and New York as the technology leader in yellow, counties of the lower 48 U.S. states

⁶ The hinge is defined as the median of the upper (lower) half of all scores.

Figure 5 shows a cartogram of technology leaders as measured by real per capita income during the 1970–2000 period, for counties of the lower 48 U.S. states, with counties exceeding the 1.5 hinge in red and New York in yellow. Throughout the entire period New York has been the technology leader, but over time it can be noticed that clusters of high per capita income counties occur close to the “global” as well as local technology leaders.⁷ Specifically, one can see little clusters around New York and Washington and around San Francisco, and incidental high per capita income counties in Colorado and Wyoming.

Table 2. Results for the endogenous growth model with diagnostics for spatial effects, and spatial process models allowing for spatial dependence and heterogeneity^a

Models	Benhabib-Spiegel			Spatial Benhabib-Spiegel		
	OLS	GM-HET		OLS	GM-HET	
Variables	(1)	slow (2a)	fast (2b)	(3)	slow (4a)	fast (4b)
Constant	0.14*** (0.01)	0.18*** (0.02)	0.53*** (0.02)	0.21*** (0.02)	0.27*** (0.03)	0.45*** (0.03)
Labor	−0.16*** (0.01)	0.02 (0.02)	−0.06*** (0.02)	−0.13*** (0.01)	0.03 (0.02)	−0.07*** (0.02)
Physical capital	0.20*** (0.01)	0.02 (0.02)	0.09*** (0.02)	0.18*** (0.01)	0.02* (0.01)	0.08*** (0.01)
Human capital	−0.02*** (0.0008)	−0.01*** (0.002)	−0.008*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)	0.001 (0.001)
Spillover human capital				−0.005*** (0.001)	−0.005*** (0.002)	0.006*** (0.002)
Spatial domestic effect				−0.02*** (0.002)	−0.01*** (0.003)	−0.02*** (0.002)
Catch-up effect	0.01*** (0.0004)	0.009*** (0.0008)	0.005*** (0.0004)	0.02*** (0.0005)	0.01*** (0.001)	0.007*** (0.001)
Spatial AR parameter		0.52*** (0.24)			0.37*** (0.13)	
R^2 adjusted ^b	0.37	0.64		0.43		
AIC	−3057.70			−3330.06		
LIK	1533.85			1672.03		
JB	19091.86***			37352.30***		
KB ^c	37.82***			34.25***		
Chow-Wald ^d		1229.51***			1651.39***	
I	0.27***			0.19***		
LM-error	2967.26***			1540.14***		
Robust LM-error	1218.00***			495.83***		
LM-lag	1936.08***			1254.79***		
Robust LM-lag	186.83***			210.48***		
LM-SARMA	3154.09***			1750.62***		

^a Standard errors in parentheses. Significance at the 1, 5 and 10% level is signaled by ***, **, and *, respectively.

^b Squared correlation for GM.

^c Koenker-Basset variant of the Breusch-Pagan test with random coefficients as the alternative hypothesis.

^d The tests on equality of individual coefficients for the different groups are all significant ($p < 0.05$) in the Benhabib-Spiegel model. In the spatial version the equality test shows $p < 0.01$, except for domestic.

⁷ Note that being the technology leader does not necessarily coincide with having the highest proportion of highly educated. For instance, in 2003 the technology leader is New York, whereas the proportion of highly educated in New York, in 2000, is 0.49 as compared to the county with the highest higher education proportion of the population, which is Los Alamos, New Mexico, where it is 0.61.

For the estimation of the model we have assembled data on labor and capital. For labor we have used BEA data on the number of full-time and part-time jobs, which is not really optimal because full- and part-time jobs are not prorated. This needs some further work in the future. For capital there is again no capital stock series available for U.S. counties. We constructed the series on the basis of the national capital stock data in constant 2003 prices (i.e., the stock of privately-owned and government-owned durable equipment and structures), which were allocated across counties using wage and salary disbursements at the county level.⁸ Distance to the technology leader is measured using arc-distance for geographical midpoints, expressed in longitude and latitude, of the counties.⁹ The technology gap is determined for the base-year, 1969. Finally, instead of the inverse distance function used in the above theoretical explanation, we implemented the empirical model using a negative exponential distance decay function given by $d_{ij}^* = a \cdot \exp(-d_{ij}/s)$, where a is fixed at unity, and s is a scaling parameter determining the spatial range over which the distance decay occurs. The value for the latter we used is 2500, which makes that the distance decay is close to complete at a distance of approximately 2500 miles (which is approximately the distance between New York and San Francisco).

Table 2 provides results using the OLS and the GM estimator, with the latter using the spatial regimes described earlier as well as groupwise heteroskedasticity. Columns (1) and (2) present the results for the original Benhabib and Spiegel model, and columns (3) and (4) for the spatial version of their model introduced above. The results shows that labor oftentimes has the wrong sign, except if a distinction is made between slow and fast growing economies, in which case the sign is correct for slow-growing economies although the coefficient is no longer significantly different from zero. For the a-spatial version of the model we find that human capital has a negative and significant effect, which corresponds to the earlier findings of Benhabib and Spiegel (1994). The catch-up effect, however, is positive. The results for the diagnostics are similar to the findings reported above for the MRW model (normality and homoskedasticity are rejected, and spatial error autocorrelation is likely to be present). Moreover, implementation of the spatial regime specification with groupwise heteroskedasticity results in coefficients unequal across regimes. The results of the spatial version of the Benhabib and Spiegel model are largely similar to the results of the a-spatial version, although there are some noteworthy exceptions. First, we now find that the effect of human capital is positive for fast-growing regions (although not significant), and that the spatial spillover effect of human capital of neighboring regions is positive (and significant) for fast-growing economies. Both are negative of no distinction between spatial regimes is made, as well as for slow-growing regions. The “domestic” effect of human capital in combination with the geographical distance to the technology leader is negative and the (absolute value of the) coefficient is of similar magnitude as for the catch-up term even although the restriction is not enforced. The catch-up term is again positive and significantly different from zero.

These preliminary results for the spatial endogenous growth model seem to indicate that it is not so much regional investment in human capital resulting in a “domestic” effect on

⁸ This allocation can be derived from profit maximization using a Cobb-Douglas production function but involves rather restrictive assumptions, such as perfect capital mobility.

⁹ We used the spherical law of cosines formula that reads as $d = R \cdot \arccos[\sin(\text{lat } 1) \cdot \sin(\text{lat } 2) + \cos(\text{lat } 1) \cdot \cos(\text{lat } 2) \cdot \cos(\text{long } 2 - \text{long } 1)]$ where R is the radius of the earth, which is fixed at 3,959 miles, and longitude and latitude are expressed in radians.

regional income growth that dominates but rather the induced effect through catch-up with the technology leader. Future improvements regarding data, model development and estimation are, however, needed to further substantiate the analysis.

6. Conclusion

In this paper we have utilized some exploratory and spatial econometric data analysis techniques to investigate issues of economic growth, human capital, and technological leadership for U.S. counties using data from 1969 through 2003. We have investigated the performance of the neoclassical Mankiw, Romer and Weil model as well as a model in which technology growth is explained on the basis of a “domestic” effect of human capital stock as well as through a process of catching-up to the technology leader. In particular we have introduced distance decay processes for both the domestic and the technology catch-up terms in order to avoid the topological invariance of the standard economic models. We find that human capital strongly contributes to growth in a neoclassical setting, but much less so in an endogenous setting. In the endogenous model the catch-up term dominates in comparison to “domestic” human capital effects, except maybe in fast-growing economies.

In the near future we will work on several issues. We will provide a more formal theoretical underpinning for the model. We will also look for improvements in the data that are needed to implement the models, and utilize spatial econometric estimators that are less restrictive (e.g., higher-order models). We are also planning on investigating whether a useful distinction can be made between local and “global” technology leaders, which is probably especially relevant in the U.S., because leading technological counties are located on the east as well as on the west coast. Finally, the data we have gathered now will make it possible to extend the analysis to a panel data setting, which is likely to improve efficiency as well as the flexibility to model contagious as well as hierarchical effects more explicitly.

References

- Abreu, M., H.L.F. de Groot and R.J.G.M. Florax (2005a) Space and Growth: A Survey of Empirical Evidence and Methods, *Région et Développement* **21**, 13–44.
- Abreu, M., H.L.F. de Groot and R.J.G.M. Florax (2005b) A Meta-Analysis of β -Convergence: The Legendary 2%, *Journal of Economic Surveys* **19**, 389–420.
- Acs, Z.J., L. Anselin and A. Varga (2002) Patents and Innovations Counts as Measures of Regional Production of Knowledge, *Research Policy* **31**, 1069–85.
- Acs, Z.J., D.B. Audretsch and M.P. Feldman (1992) Real Effects of Academic Research, *American Economic Review* **82**, 363–67.
- Anselin, L. (1996) The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association, in: M. Fischer, H. Scholten and D. Unwin (eds.), *Spatial Analytical Perspectives on GIS*, London: Taylor and Francis.
- Anselin, L., A. Bera, R. Florax and M. Yoon (1996) Simple Diagnostic Tests for Spatial Dependence, *Regional Science and Urban Economics* **26**, 77–104.
- Anselin, L., A. Varga and Z. Acs (1997) Local Geographic Spillovers between Universities Research and High Technology Innovations, *Journal of Urban Economics* **42**, 422–48.
- Audretsch, D.B. and M. Feldman (1996), R&D Spillovers and the Geography of Innovation and Production, *The American Economic Review* **86**, 630–40.
- Audretsch, D.B. and M. Keilbach (2004) Entrepreneurship Capital and Economic Performance, *Regional Studies* **38**, 949–59.

- Barro, R.J. and X. Sala-i-Martin (1991) Convergence across States and Regions, *Brookings Papers on Economic Activity* **1**, 107–58.
- Becker, G.S. (1975) *Human Capital*, Chicago: The University of Chicago Press.
- Benhabib, J. and M. Spiegel (1994) The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data, *Journal of Monetary Economics* **34**, 143–73.
- Bell, K. and N. Bockstael (2000) Applying the Generalized Moments Estimation Approach to Spatial Problems Involving Microlevel Data, *The Review of Economics and Statistics* **82**, 72–82.
- Carlino, G.A. and E.S. Mills (1987) The Determinants of County Growth, *Journal of Regional Science* **27**, 39–54.
- Carlino, G.A. and L.O. Mills (1993) Are U.S. Regional Incomes Converging? A Time Series Analysis, *Journal of Monetary Economics* **32**, 335–46.
- Cliff, A. and J. Ord (1981) *Spatial Processes, Models, and Applications*, London: Pion.
- Coe, D.T. and E. Helpman (1995) International R&D spillovers, *European Economic Review* **39**, 859–87.
- Egger, P. and M. Pfaffermayer (2006, forthcoming) On the Role of Regional Spillovers for Beta and Sigma-Convergence, *Papers in Regional Science*.
- Ertur, C. and W. Koch (2005) Growth, Technological Interdependence and Spatial Externalities: Theory and Evidence, paper presented at the 45th congress of the European Regional Science Association, Amsterdam, The Netherlands.
- Ertur, C. and W. Koch (2006) Convergence, Human Capital and International Spillovers, paper presented at the International Workshop on Spatial Econometrics and Statistics, Rome, Italy.
- Feldman, M. (1994) *The Geography of Innovation*, Dordrecht: Kluwer.
- Fujita, M., P. Krugman and A.J. Venables (1999) *The Spatial Economy: Cities, Regions and International Trade*, Cambridge, MA: MIT Press.
- Garofalo, G.A. and S. Yamarik (2002) Regional Convergence: Evidence from a New State-by-State Capital Stock Series, *The Review of Economics and Statistics* **84**, 316–23.
- Grossman, G.M. and E. Helpman (1990) Trade, Innovation and Growth, *American Economic Review* **80**, 86–91.
- Grossman, G.M. and E. Helpman (1994) Endogenous Innovation in the Theory of Growth, *Journal of Economic Perspectives* **8**, 23–44.
- Higgins, M., D. Levy and A. Young (2006, forthcoming) Growth and Convergence across the U.S.: Evidence from County Level-Data, *Review of Economics and Statistics*.
- Holtz-Eakin, D. (1993) Solow and the States: Capital Accumulation, Productivity, and Economic growth, *National Tax Journal* **46**, 425–39.
- Islam, N. (2003) What Have We Learnt from the Convergence Debate? *Journal of Economic Surveys* **17**, 309–62.
- Jaffe, A.B. (1989), Real Effects of Academic Research, *American Economic Review* **79**, 957–970.
- Kelejian, H.H. and I.R. Prucha (1999) A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model, *International Economic Review* **40**(2): 509–33.
- Kelejian, H.H. and I.R. Prucha (2005) Specification and Estimation of Spatial Autoregressive Models with Autoregressive and Heteroskedastic Disturbances, manuscript, University of Maryland.
- Krugman, P. (1991) Increasing Returns and Economic Geography, *Journal of Political Economy* **99**, 483–99.

- Magrini, S. (2004) Regional (Di)Convergence, in: V. Henderson and J.F. Thisse (eds.), *Handbook of Urban and Regional Economics*, Volume 4, Amsterdam: Elsevier.
- Mankiw, N.G., D. Romer and D. Weil (1992) A Contribution to the Empirics of Economic Growth, *Quarterly Journal of Economics* **107**, 407–37.
- Nelson, R. and E. Phelps (1966) Investment in Humans, Technological Diffusion, and Economic Growth, *American Economic Review* **56**, 65–75.
- Parent, O. and S. Riou (2005) Bayesian Analysis of Knowledge Spillovers in European Regions, *Journal of Regional Science* **45**, 747–75.
- Rey, S.J. and B.D. Montouri (1999) U.S. Regional Income Convergence: A Spatial Econometric Perspective, *Regional Studies* **33**, 143–56.
- Rey, S.J. and M.V. Janikas (2005) Regional Convergence, Inequality, and Space, *Journal of Economic Geography* **5**, 155–76.
- Romer, P. (1986) Increasing Returns and Long Run Growth *Journal of Political Economy* **97**, 1002–37.
- Romer, P.M. (1990) Endogenous Technological Change, *Journal of Political Economy* **98**, 71–102.
- Solow, R.M. (1956) A Contribution to the Theory of Economic Growth, *The Quarterly Journal of Economics* **32**, 185–94.
- Swan, T.W. (1956) Economic Growth and Capital Accumulation, *Economic Record* **32**, 334–61.
- Tiefelsdorf, M. (2000) *Modelling Spatial Processes: The Identification and Analysis of Spatial Relationships in Regression Residuals by Means of Moran's I*, Heidelberg: Springer-Verlag.